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Multiscale modeling of the Cocktail Party Problem

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Problem statement

Sounds in everyday life seldom exist in isolation. We are constantly surrounded by a cacophony of sounds that constantly impinge on our ears

☛ **Cocktail Party Problem (CPP)**

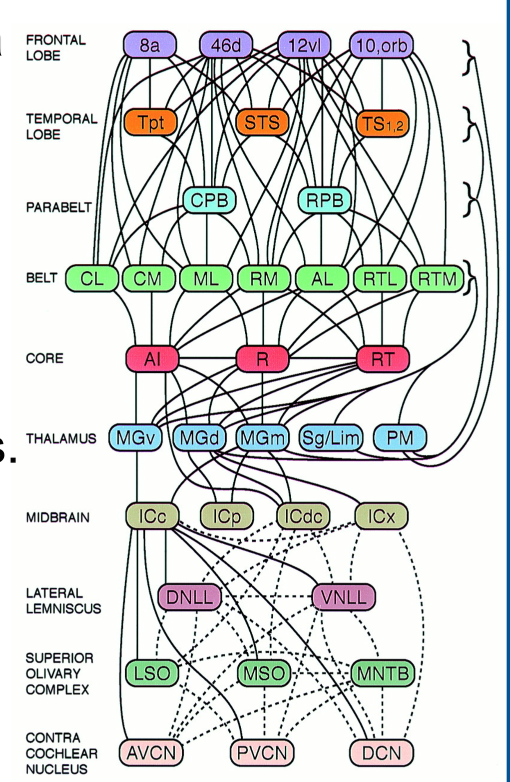
Medical & Engineering relevance:

- ✓ Hearing prostheses
- ✓ Audio technologies
- ✓ Communication systems
- ✓ Medical diagnosis
- ✓ Microphone Design

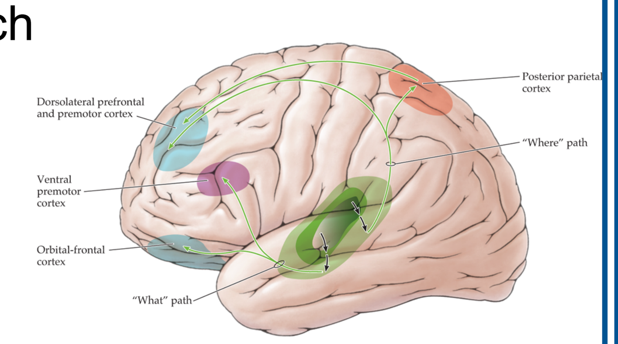
...

Multiscale Approach

- An acoustic signal undergoes a series of transformations from the cochlea all the way to auditory cortex, effectively extracting a rich feature representation that forms the basis for perceptual representation of sound objects.
- These transformations evolve along multiple spectral and temporal scales and engage local and global neural circuits

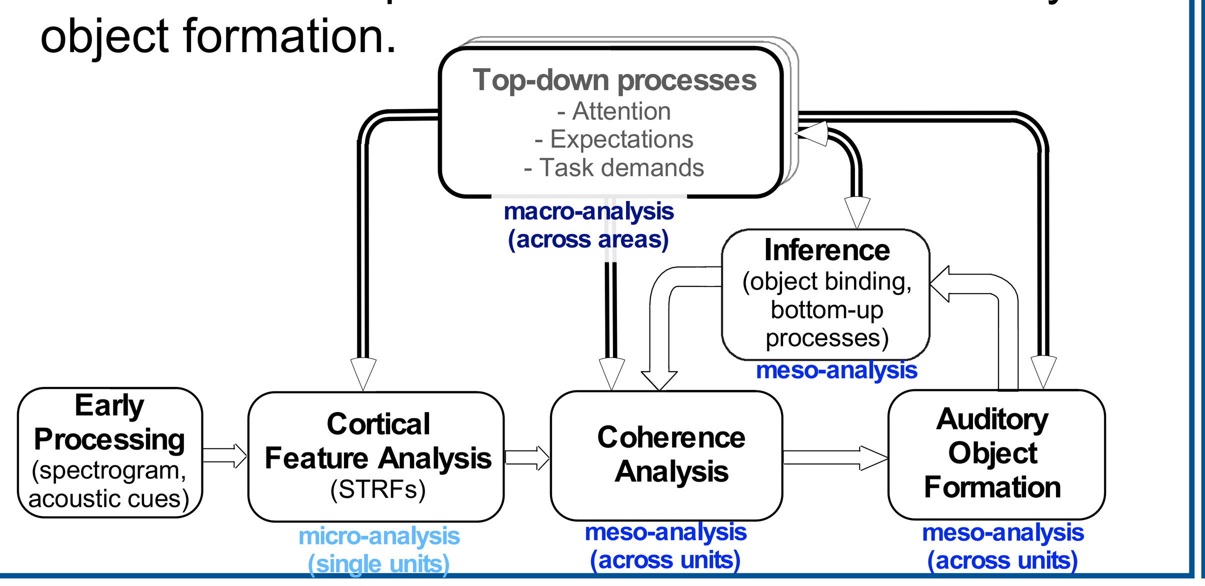


The current project puts forth an **adaptive theory of auditory perception** which integrates the role of *both* sensory mechanisms and cognitive control in a unified multiscale scheme.

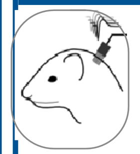


Multiscale modeling:

- *Micro-level* analysis of complex sounds (at the single neuron level) into a multidimensional space
- *Meso-level* group analysis correlating activity in populations of cortical neurons (bottom-up)
- *Macro-level* (across-area) feedback processes of attention and expectations that mediate auditory object formation.

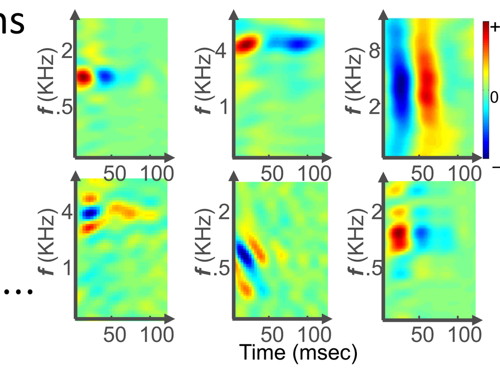


Statistical inference of sound



- **Modeling neural response properties**
  - At level of individual neurons
  - Across neural populations

$$r(t) = \vartheta_0 + \int_{-\infty}^{\infty} \vartheta_1(\tau)s(t-\tau)d\tau + \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \vartheta_2(\tau_1,\tau_2)s(t-\tau_1)s(t-\tau_2)d\tau_1 d\tau_2 + \cdots$$



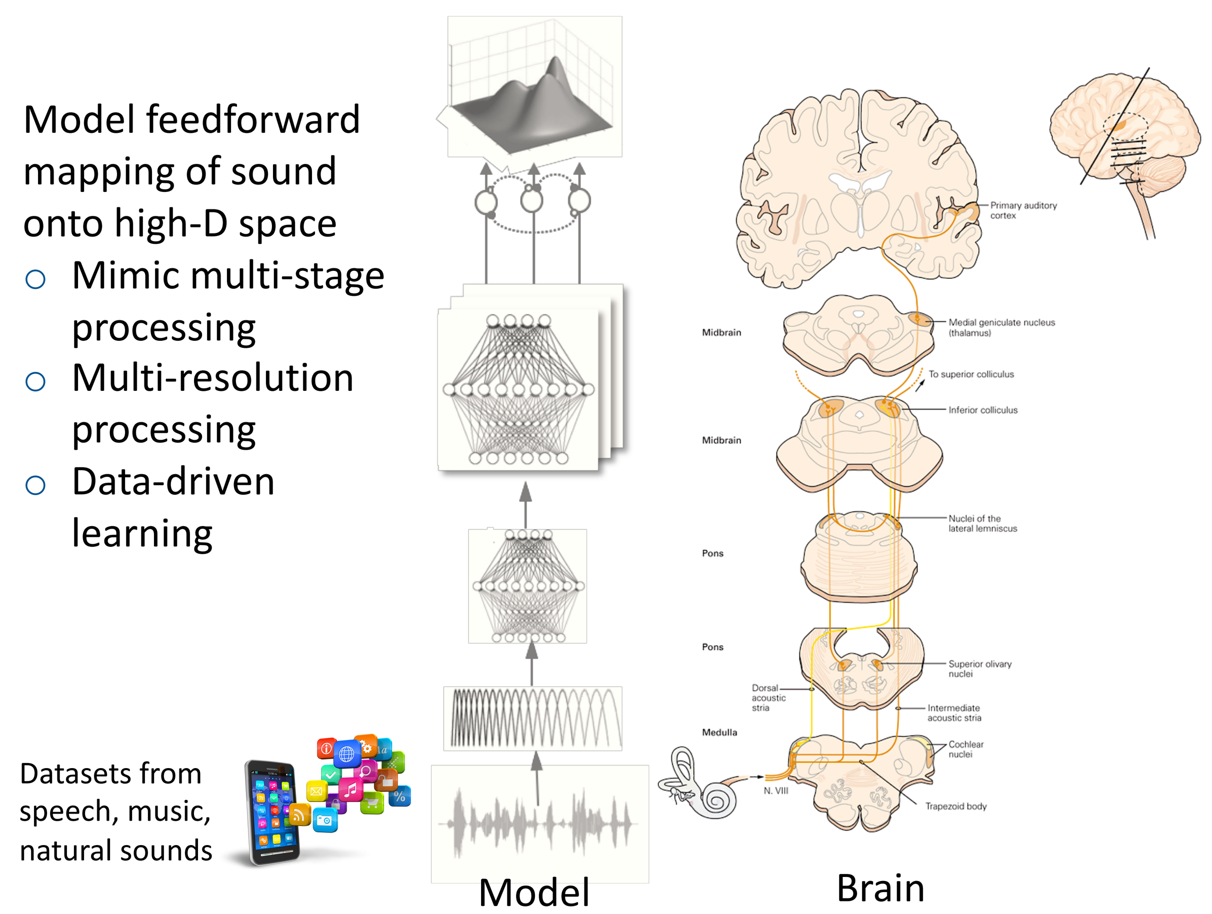
$$\boldsymbol{r(t) \approx \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \vartheta_2(\tau_1,\tau_2)s(t-\tau_1)s(t-\tau_2)d\tau_1 d\tau_2}$$

Linear approximation using 2nd order Volterra kernel

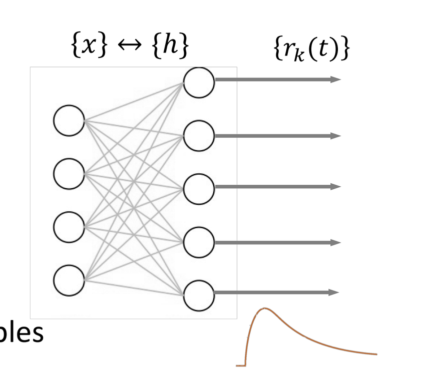
- **Mapping into a high-D statistical space**

Model feedforward mapping of sound onto high-D space

- Mimic multi-stage processing
- Multi-resolution processing
- Data-driven learning



- **Local scale analysis**
  - Sparse **R**estricted **B**oltzmann **M**achine
    Generative stochastic network
    ⇨ **Discover** structure in the data
    Infer **probabilistic distribution** over hidden variables



$$P(x,h) = \frac{1}{Z}e^{-E(x,h)}$$

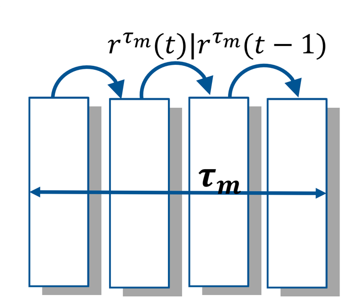
Decaying energy fct.

normalization

Once trained, weight connections are converted into STRFs $\psi(.)$

$$r_k(t) = \sum_f \int S_i(\tau,f).\psi(t-\tau,f)d\tau$$

- **Global scale analysis**
  - Conditional **R**estricted **B**oltzmann **M**achine
    Generative stochastic network
    Incorporates 'priors' from activations over recent past $\boldsymbol{\tau_m}$



$$P(r(t),h(t)|\vec{r}(t)) = \frac{1}{Z}e^{-E\left(r(t),h(t)|\vec{r}(t)\right)}$$

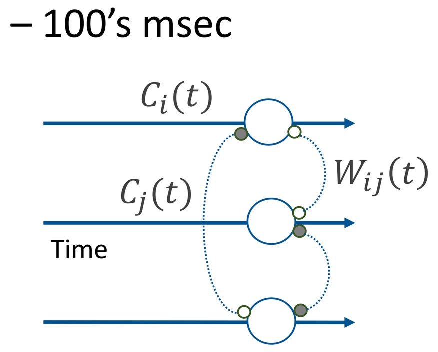
Decaying energy fct.

Sequential integration over 10's – 100's msec

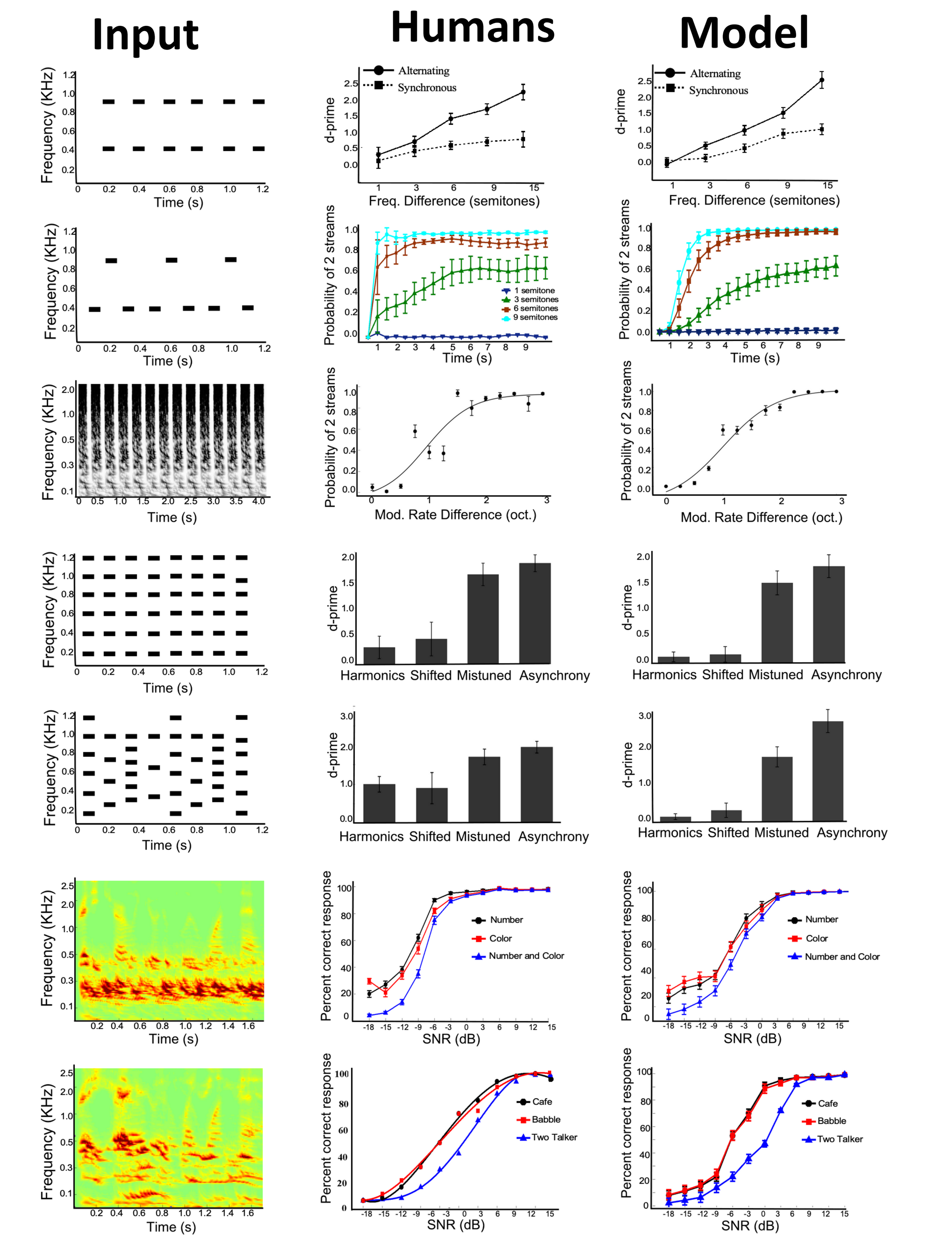
- **Macro-scale integration**

$$W_{ij}(t) = \zeta W_{ij}(t-1) + \xi C_i(t)C_j(t)$$

Hebbian learning



Model Validation

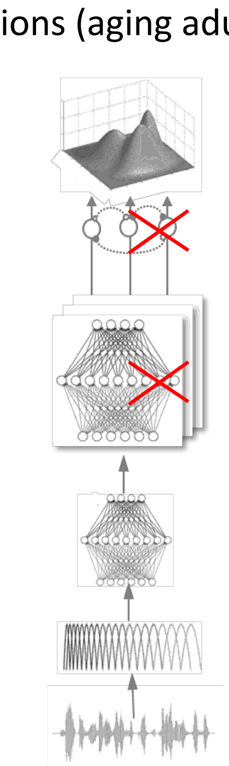


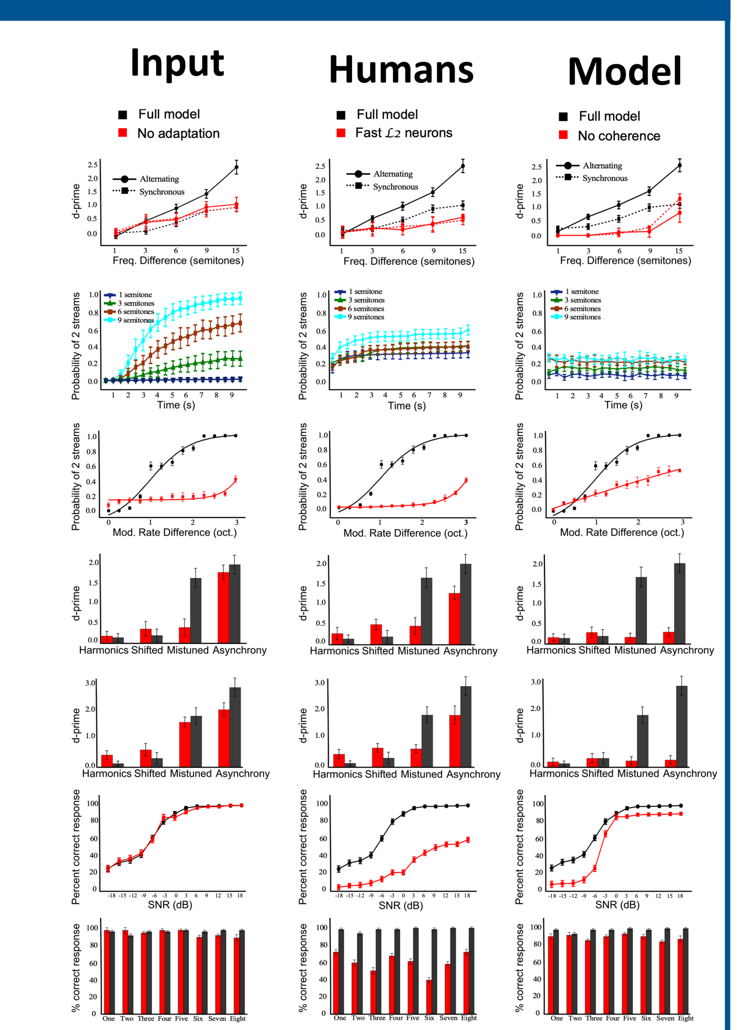
Model Credibility

- **Context:** Multiscale model for auditory stream segregation
- **Data**: Perception of simple and complex sounds by human listeners
- **Evaluation**: Fixed model tested with exact stimuli used for human listeners
- **Limitations**: Model is feedforward with no contextual knowledge (language, memory)
- **Version control** : Implementation history and functionality are documented
- **Dissemination**: Model is publicly shared online, along with peer-reviewed paper
- **Competition**: Model used as backbone for open competition on auditory event detection (DCASE - IEEE AASP Challenge on Detection and Classification of Acoustic Scenes and Events)
- **Opportunities**: Springboard to expand into multiple neural scales and explore effects of feedback interactions (top-down/bottom-up)

Model function and malfunction

Modify model structure to test limitations, necessary and sufficient processes as well as explore implications for special populations (aging adults)

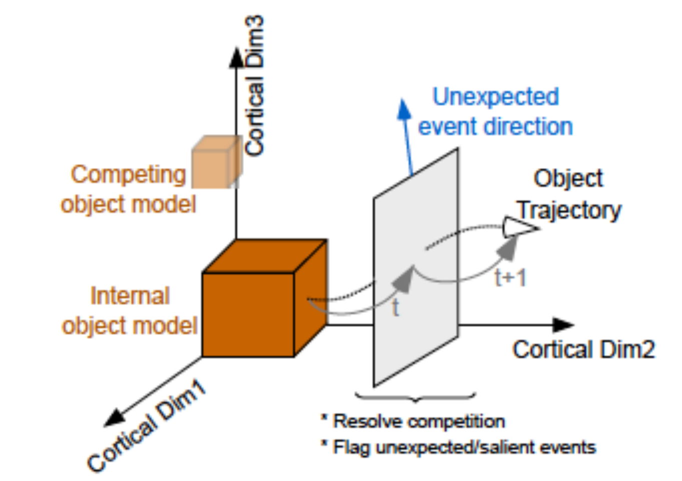




Cognitive control

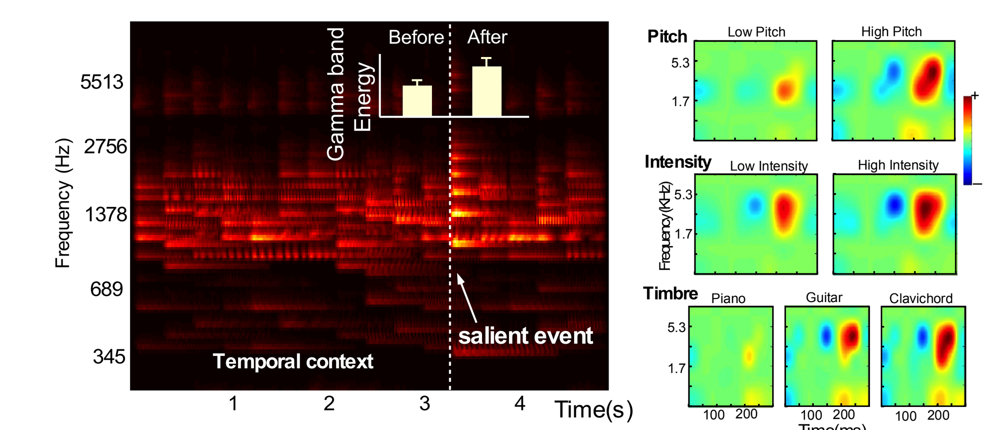
- **Role of working memory and bottom-up attention**

Tracking of sound elements in the cortical high-D space operates as a Bayesian inference process.



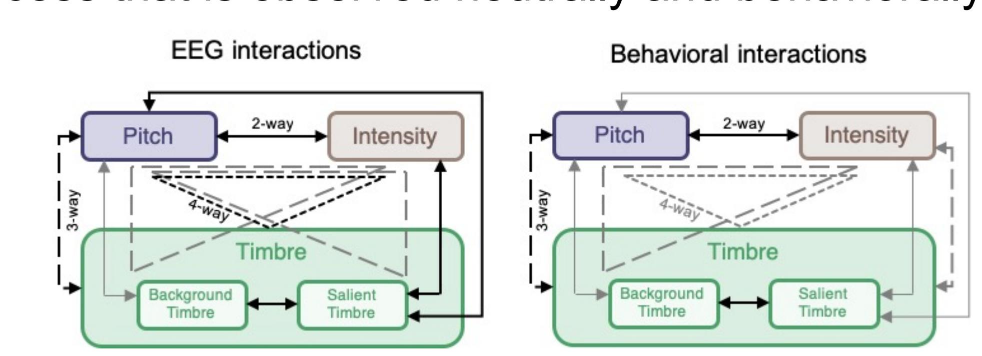
Human listeners tracking dynamical scenes show sensitivity to changes in:

- ✓ Mean and variance changes of acoustic features
- ✓ High-order statistics of individual features



Changes in neural responses (EEG) of dynamic scenes driven by bottom-up attention

Integration across acoustic attributes is a nonlinear process that is observed neutrally and behaviorally



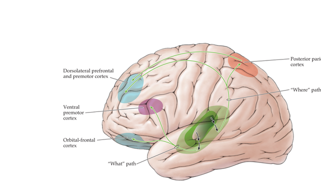
Ongoing efforts

A dynamical systems model is flexible framework to explore

- Statistical inference
- Bayesian tracking
- Multi-scale integration

Considerations/ongoing efforts

- Assumptions of stationarity need to be examined (adaptive coding)
- Translation of memory (short and long) onto attentional feedback signals and its integration in the scheme
- Interplay of bottom-up and top-down feedback



Model implications and validation

- Ongoing tests of model credibility
- Experimental predictions (e.g. how feedback shapes sensory processing)

References

- Chakrabarty, D. & Elhilali, M. "A Gestalt inference model for auditory scene segregation". *PLOS Comp. Bio* 15(1):e1006711, 2019.
- Kaya EM, Huang N, Elhilali M "Neural signature of salience in natural auditory scenes", *under review.*
- Huang N, Elhilali M "Bottom-up and top-down auditory attention", *under review.*

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